EJTIR

Issue 15(3), 2015
pp. 304-316
ISSN: 1567-7141
tlo.tbm.tudelft.nl/ejtir

How uncertainty in socio-economic variables affects large-scale transport model forecasts

Stefano Manzo [1]
Department of Transport, Technical University of Denmark

Otto Anker Nielsen [2]
Department of Transport, Technical University of Denmark

Carlo Giacomo Prato[3]
Department of Transport, Technical University of Denmark

A strategic task assigned to large-scale transport models is to forecast the demand for transport over long periods of time to assess transport projects. However, by modelling complex systems transport models have an inherent uncertainty which increases over time. As a consequence, the longer the period forecasted the less reliable is the forecasted model output. Describing uncertainty propagation patterns over time is therefore important in order to provide complete information to the decision makers. Among the existing literature only few studies analyze uncertainty propagation patterns over time, especially with respect to large-scale transport models. The study described in this paper contributes to fill the gap by investigating the effects of uncertainty in socio-economic variables growth rate projections on large-scale transport model forecasts, using the Danish National Transport Model as a case study. Population, gross domestic product, employment, and fuel prices were analyzed to quantify their uncertainty for 5 year intervals over a period of 15 years. The output of this procedure was then used to implement model sensitivity tests. The results from the model sensitivity tests showed how the model output uncertainty grows over time, reflecting the increase in the uncertainty of the model variables. Furthermore, the resulting uncertainty temporal pattern was neither linear nor similar for the different model outputs investigated. This highlights the importance of investigating uncertainty for different model outputs, and also that a dynamic approach is required whenever the model has to provide mid-long time period forecasts.

Keywords: *large-scale transport models, forecasts, Monte Carlo simulation, sensitivity tests, stochastic variables, uncertainty.*

1. Introduction

Transport models are of great importance within transport project appraisals, since they provide insight into the demand responsiveness to changes in the transport system. This is true for all kind of appraisals, such as scenario-based forecasting studies, referring for instance to a national or regional master plan, or more general supply oriented analyses, referring for instance to

[1] A: Bygningstorvet 116B, 2800 Kgs. Lyngby, Denmark T: +45 45 25 15 54 E: stman@transport.dtu.dk
[2] A: Bygningstorvet 116B, 2800 Kgs. Lyngby, Denmark T: +45 45 25 15 14 E: oan@transport.dtu.dk
[3] A: Bygningstorvet 116B, 2800 Kgs. Lyngby, Denmark T: +45 45 25 65 95 E: cgp@transport.dtu.dk

infrastructural changes. Usually transport projects have a medium-long run perspective, which might easily go up to 30 years. This is not only because they require long time to be implemented, but also because transport demand needs time to adjust to changes on the supply side. Therefore, a key purpose of transport models, and in particular of large-scale models, is their ability to forecast the transport demand over medium to long time periods.

However, a reason of concern is the inherent uncertainty of the input variables included in transport models. Uncertainty refers to any component of the system object of the modelling process that the modeller does not know to a full extent and, consequently, is not able to thoroughly reproduce in the model. A specific issue is that the modeller's knowledge about the characteristics of the model components, such as context, inputs, etc., decreases the further the model forecasts are away from the present state. This is particularly true for the model variables that describe the external forces that produce changes in the reference system, such as the future values of the model socio-economic variables. Consequently, it can be argued that model output uncertainty varies over time. For this reason, as pointed out by De Jong et al. (2007), defining the path of how model output uncertainty changes over time is of great importance. Allowing the inclusion of the levels of future uncertainty into the projects selection criteria would in fact guarantee a better comparison of alternative projects.

The rationale behind the present study is twofold. First, it aims to provide insight with respect to how uncertainty in growth rate projections of socio-economic variables varies over time and into the effects of this variation on large-scale transport model forecasts. Secondly, it aims to outline a method to carry out such analysis by implementing a Monte Carlo simulation dynamic approach to compute and describe how uncertainty, represented in the Monte Carlo simulation by the variables' Standard Deviation (SD), varies over time.

The Danish National Transport Model (NTM) is used as a case study. The analysis focused on the uncertainty in the forecasted growth rates of the following socio-economic variables: population, Gross Domestic Product (GDP), employment and fuel prices. Uncertainty was quantified for 5 year intervals over a period of 15 years, producing SD of the variables forecasts. Monte Carlo simulation was then implemented using the official growth rates forecasts as mean values combined with the estimated SD. The 5, 50 and 95 percentiles resulting from the probability distributions of the variables investigated were then used to run sensitivity tests on the NTM.

The following section 2 of this paper provides a literature review on the subject, while section 3 describes the NTM. Section 4 illustrates the methodology applied in this study. Results and conclusions are discussed in the last two sections of the paper.

2. Literature review

The literature on uncertainty in transport models investigates both the sources and the effects of uncertainty in transport models; thorough reviews of such literature can be found, for instance, in De Jong et al. (2007) or Rasouli and Timmermans (2012). With respect to the model components, the literature investigated the uncertainty of the model input (i.e., the model exogenous variables), model parameters (i.e., the model calibrated parameters), or both. However, only a few papers focus on uncertainty deriving from the model input alone, such as Leurent (1996) and Rodier and Johnston (2002). Instead, the majority of the existing literature focused on both model input and parameters uncertainty, as in Ashley (1980), Kroes (1996), Zhao and Kockelman (2002), Pradhan and Kockelman (2002), Krishnamurty and Kockelman (2003), Armoogum (2003), De Jong et al. (2007), Matas et al. (2011) and Zhang et al. (2011). Finally, some papers focused on model parameters uncertainty, such as Brundell-Freij (2000), Hugosson (2005) and Petrick et al. (2012).

Nevertheless, only a few papers investigated transport model uncertainty by quantifying the uncertainty propagation pattern over time. Rodier and Johnston (2002) implemented a scenario analysis on the travel demand and emission model of the Sacramento region (USA). They defined uncertainty margins for the variable forecasts through the study of existing forecasts and time series, and performed sensitivity tests for two years, 2005 and 2015. The results show an increase in uncertainty from 2005 to 2015 for all the model output analysed. Pradhan and Kockelman (2002) applied a factorized design approach to quantify uncertainty in the land use variables of an integrated land use-transport model. The sensitivity tests, implemented over a 15 years period, show that model output uncertainty increases over the first 10 years to then reduce in the last 5 years, arguably due to model adaptation. Krishnamurty and Kockelman (2003) investigated uncertainty in the Austin transportation model through Monte Carlo simulation. They calculated uncertainty pattern over 15 years for peak and off peak vehicle hours and vehicle miles travelled. The results show an increase in uncertainty throughout the time period analysed. Matas et al. (2011) implemented an uncertainty analysis on traffic forecasts for the Spanish tolled motorway network over a 15 years period. Uncertainty in model input and parameters was quantified through Bootstrap re-sampling method. Results show an increase on the overall model uncertainty over the period. Thus, all the existing studies showed an increase over time of model output uncertainty. However, with the partial exception of Rodier and Johnston (2002), none of the aforementioned studies explicitly addressed the variation of uncertainty over time. In fact, the increase of model output uncertainty was related to the growth in the variables mean value over time and not in the variance, say, uncertainty, around these values, which was kept constant by the authors.

Another thing worth to be noted is that not many papers implemented their analyses by using large-scale transport models as case studies. The few exceptions include Hugusson (2005), which used the Swedish National Travel Demand Forecasting System, “Samper”, and De Jong et al. (2007) which run their analysis on the Dutch national model system, the Landelijk Model Systeem. Finally, as previously said, Matas et al. (2011) based their work on the Spanish tolled motorway network.

3. Case study – The Danish National Transport Model (NTM)

The NTM is a large scale transport model that has been developed for the Danish Ministry of Transport with the intention of providing a tool to be used for all transport project evaluations in Denmark (Rich et al. 2010) at both national and regional levels. The NTM combines several sub-models, as graphically described in Figure 1. Preliminarily, the model exogenous variables, such as population, transport networks and employment, are defined. Afterwards, in the step called population synthesis, a population matrix is created through the forecasting methodology described later. Then, the framework divides in two parallel demand models: the passenger and the freight demand models. The output of these models feeds the multimodal assignment models (including walk, bike, public transport, rail, car driver, car passenger and air), which is the last stage of the framework. The assignment models set the level of service per modes and routes by assigning traffic to the physical network at the link level. The level of service is then fed back to the passenger demand models, in an iterative process which ends when equilibrium between demand and assignment is achieved. Currently this is accomplished through a heuristic approach based on a weighted method of successive averages. Overall, the model comprises more than 18 different sub models for different trip segments and durations and whether or not trips outside Denmark are included.

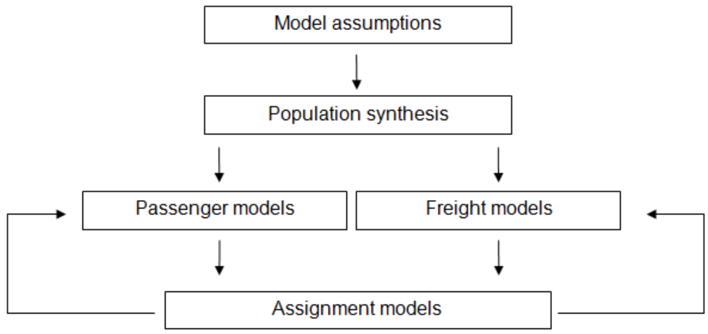

Figure 1. The Danish National Transport Model framework

The passenger demand models are tour-based: the demand of transport is modelled as a sequence of trips, modelling the primary activity of the day and the intermediate stop activities (conditional on the primary activity), starting and ending in the same location. The models thus describe several trip purposes, the choice of trip frequency and destination. In the NTM, the zone system is based on four different aggregation levels, going from the more aggregated (municipality level, 98 zones) to the more disaggregated (regional level, 3670 zones). The road network consists of 34224 links.

The forecasting methodology for the socio-economic variables in the NTM is based on the Prototypical Sample Enumeration (PSE) approach (Daly, 1998) implemented through an iterative proportional fitting matrix estimation method. The PSE fits the baseline information (e.g., resulting from a survey) to the population profile (target) created by using socio-economic forecasts or assumed scenarios. Eventually, the PSE creates a weighted version of the baseline information which is representative of the population profile (Rich, 2011). In the NTM, the population baseline information matrix combines three main datasets: demographic, GDP and employment which are then combined with information regarding the households. The information comes from the Danish national register, which provides data regarding individuals, such as employment status and age, households, such as number of children and income, and firms, such as number of employees and economic sectors. With respect to the population profile, the population forecasts are based on the forecasts from Statistics Denmark (the Danish Bureau of Statistics), while the economic profiles, based on GDP, employment and level of productivity by sector forecasts, are based on the forecasts of the Danish Ministry of Economics. The overall procedure is graphically described in Figure 2.

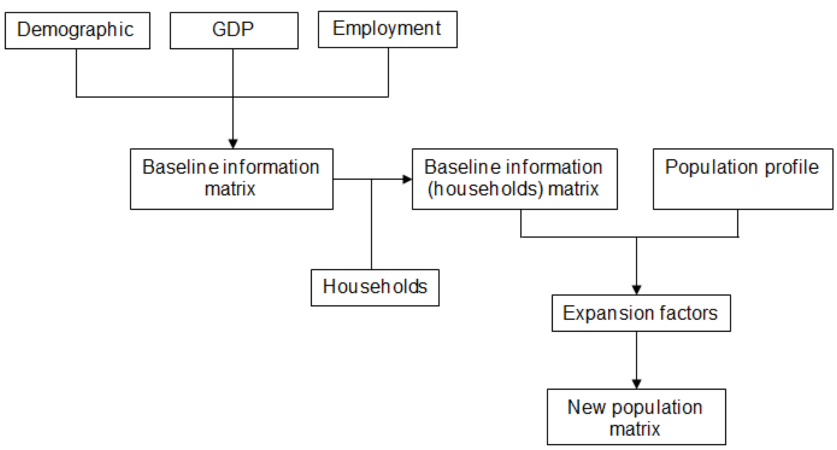

Figure 2. NTM forecast framework

4. Methodology for uncertainty analysis of the input variables

Within uncertainty analysis it is common practice to select, for instance through preliminary sensitivity tests, the key model variables to investigate. The study described in this paper does not implement such selection. It focuses instead on the combined effect of the uncertainty deriving from the variables investigated, irrespective to the sensitivity the model shows to each of them separately. Furthermore, the analysis investigated the NTM socio-economic variables that have documented and available annual growth rate time series and forecasts, i.e. the population, employment, GDP (real) and fuel prices (both petrol and diesel). In particular, the focus of the analysis was on the uncertainty of the growth rate forecasts over a period of 15 years, from 2010, which corresponds to the NTM base year, to 2025. Data referring to the population, employment and GDP are used by the NTM in the PSE and, with respect to employment levels per zone, as zone attraction variable. The GDP values and the fuel prices, from the Danish oil industry association, are used to define, respectively, the value of time and the cost of travel per kilometre.

The uncertainty in the other NTM socio-economic variables, such as population spatial distribution, income distribution, work productivity and car ownership, was not explicitly investigated for different reasons. The analyses of the population spatial distribution and of the income distribution would require a scenario analysis approach which would not fit the stochastic Monte Carlo simulation analysis implemented for this study. The levels of work productivity depend on improvement in factors affecting production processes, such as technological innovation or more efficient corporate governance structures, which cannot be inferred from the observation of the past. In other words, according to the uncertainty taxonomy proposed by Walker et al. (2003), we are in condition of recognized ignorance. Therefore, to run the sensitivity tests the forecasted work productivity growth rates produced by the Danish Ministry of Economics were applied. Finally, car ownership (similarly to value of time) is estimated internally to the NTM, based on households characteristics, so its value reflects the uncertainty in the other socio-economic variables.

In order to quantify uncertainty in the variables' growth rate forecasts, multivariate normal Monte Carlo simulation was implemented by using Latin Hypercube sampling. In the Monte Carlo simulation, the choice of the distribution to be used in the sampling procedure is of crucial importance to correctly reflect the level of the variables' uncertainty. For the present study, the normal distribution was chosen for the following reasons. Firstly, given that in this study the variables investigated are annual growth rate forecasts, it was necessary to choose a distribution allowing representing both increases and decreases in the future values of the variables. Secondly, there was the necessity to choose a distribution symmetric around the mean and unbiased with respect to the possibility of drawing positive and negative values, given that we did not have prior expectations on that matter. Thirdly, the normal distribution allows reproducing a domain where values are not bounded between defined thresholds (due to the asymptotic tails of the distribution). Finally, the normal distribution emphasizes the likeliness of occurrence of the mean, and of the values around the mean, thus implying a degree of reliability of the forecasts, which we have no reason to doubt.

To implement the Latin Hypercube sampling, the official variables' annual growth rate forecasts for the years 2015, 2020, and 2025 were used as mean values. To describe the uncertainty pattern over time, the SD were produced for the years 2015, 2020 and 2015. Two different approaches were applied. With respect to the population, inspired by Rodier and Johnston (2002), the SD were quantified based on the difference between the forecasts published in the Statistical yearbooks by Statistics Denmark from 1980 to 2005 and the observed population. First, the percentage difference of the population forecasts was calculated for each available 5, 10 and 15 year intervals. For instance, with respect to the forecasts published in 1980 for population in 1985 the percentage difference (PD) was estimated as follows:

$$PD_{1980/1985} = (\text{Forecast}1980_{1985} - \text{Observed}_{1985})/100 \quad (1)$$

The resulting values are shown in the Table 1.

These values, grouped for intervals of 5, 10 and 15 years, were then used to calculate the SD, shown in Table 2, used as a proxy for the population growth rates uncertainty in the Monte Carlo simulation. For instance, the SD for the 2015 population annual growth rate was calculated as follows:

$$SD_{Pop2015} = SD(\text{PD}_{1980/1985}, \text{PD}_{1985/1990}, \text{PD}_{1990/1995}, \text{PD}_{1995/2000}, \text{PD}_{2005/2010}) \quad (2)$$

Table 1. Danish population: resulting percentage differences between forecasted and observed values for 5 years intervals

Forecasts publication year	Forecasted year				
	1985	1990	1995	2000	2010
1980	1.5%	2.1%	1.4%		
1985		-1.3%		-7.6%	
1990			-0.8%	-2.8%	
1995				-0.3%	-2.3%
2000					-0.7%
2005					-1.8%

With respect to the GDP, employment and fuel price growth rates, past forecasts were not available, so the SD were instead calculated based on the analysis of the annual growth rates time series. The method applied was the following. Having 2010 as NTM base year, the SD for the 2015 annual growth rate forecast was quantified based on the analysis of the annual growth rate time series referring to the period 2005-2010 (i.e. 5 years before the model base year). For 2020 and 2025 SD was quantified instead based on the time series referring, respectively, to the period 2000-2010 and 1995-2010 (i.e. 10 and 15 years before the model base year).

For instance, with respect to GDP, the SD to be used for 2015 was calculated based on the GDP annual growth rates for the period 2005-2010, as follows:

$$SD_{GDP2015} = SD(\text{GDP}_{2009/2010}, \text{GDP}_{2008/2009}, \text{GDP}_{2007/2008}, \text{GDP}_{2006/2007}, \text{GDP}_{2005/2006}) \quad (3)$$

This approach is meant to reflect a variation of the level of uncertainty throughout the forecasted period. Indeed, if the near future can be reasonably expected to be similar to the near past, the further in the future the model forecasts the broader is the range of events potentially occurring. These potential events require to be taken into consideration and, for this reason, events from a longer period in the past are included in the modelling process. For the present case study, this approach flattened or decreased the variability, expressed in terms of SD, of some of the forecasted variable values over time. This result is however expected, given the recent economic fluctuations which are foreseen to flatten in the near-mid future. As pointed out by De Jong et al. (2007), in the long run the economic variables might experience both periods of high and low growth, because of economic cycles. Thus, deriving SD from longer time series period tends to smooth the results. The mean values, i.e. the forecasted percentage growth, and the estimated SD of the variables used in the Latin Hypercube sampling are summarized in Table 2.

Table 2. Summary table of the inputs used to run the Latin Hypercube sampling on the NTM socio-economic variables

	2015		2020		2025	
	Mean	SD	Mean	SD	Mean	SD
Population	0.3	1.2	0.3	2.5	0.4	4.5
GDP	1.8	3.5	1.7	2.5	1.0	2.3
Employment	0.6	2.7	0.5	1.9	0.1	1.8
Petrol prices	-1.2	5.9	0.9	5.2	0.6	6.0
Diesel prices	-1.3	11.0	1.0	9.3	0.7	9.7

The correlation coefficients used in the Latin Hypercube sampling for GDP, population, employment, petrol and diesel growth rates values were estimated from the analysis of 30 years growth rates time series. Following a standard procedure, the variable correlations were tested for linearity, by comparing Spearman and Pearson correlation coefficients. The hypothesis of non-linearity was rejected and Pearson coefficients, summarized in Table 3, were then used for the sampling. However, only correlation coefficients between GDP and employment (+0.859) and petrol and diesel prices (+0.774) were found significant at the 0.05 level and thus used to implement the Latin Hypercube sampling.

Table 3. Pearson correlation coefficients of the NTM socio-economic variables

	GDP	Population	Employment	Petrol	Diesel
GDP	1				
Population	-0.345	1			
Employment	0.859*	-0.313	1		
Petrol prices	0.209		0.160	1	
Diesel prices	0.175		0.176	0.774*	1

* Significant at 0.05

Finally, the multivariate normal Latin Hypercube sampling was run by using the mean values and the SD from Table 2 and the correlation coefficients from Table 3. The p5 and p95 values of the distributions obtained from the Latin Hypercube sampling procedure, representing the annual growth rates for the selected years and shown in Table 4, were then used to run the sensitivity tests on the NTM along with the p50 which, as previously said, represents the variables' annual growth rate official forecasts.

Table 4. p5 and p95 NTM socio-economic variable annual growth rates used to run the sensitivity tests

	2015		2020		2025	
	p5	p95	p5	p95	p5	p95
Population	-1.7	2.3	-3.7	4.4	-7.1	7.8
GDP	-3.0	6.5	-2.5	5.9	-2.7	4.7
Employment	-3.8	5.0	-3.0	4.0	-3.0	3.1
Petrol prices	-11.0	8.5	-7.6	9.4	-9.3	10.5
Diesel prices	-19.4	16.7	-14.4	16.3	-15.3	16.7

One interpretative issue rises from this approach. For instance, the p95 model run simulates an increase in all the variable values. However, the effects of these values on the model output are of opposite sign. In fact, whilst a growth in population, employment and GDP is expected to increase the overall demand of transport, an increase in fuel prices, by increasing the cost of travel per kilometre, is of course expected to reduce it. However, the present study is interested in testing the overall effect of the uncertainty of these variables on the model output rather than decoupling their influence. Another reason of concern is that increases and decreases in oil prices, represented by increases and decreases in petrol and diesel prices, can reasonably be expected to have, respectively, negative and positive effects on the economy. However, economy needs time to adjust, thus this effects can expected to be observed in the following rather than in the very same year. This might also explain why the annual growth rate time series did not show significant correlation between the economic variables, i.e. GDP and Employment, and petrol and diesel prices. However, to take into account this issue, selected scenario analyses were implemented, as described in the last part of this paper.

All the other variables used in the NTM such as, for instance, public transport fares and network design, were left unvaried. Afterwards, the results were compared with the 2010 NTM “base” output, as described in the following section.

5. Results and discussion

The analysis was carried out with respect to the following transport modes: car driver, car passenger, public transport, bike and walk. The results from the sensitivity tests referring to the total number of trips for all modes and vehicle-kilometres (Veh-km) for motorized modes are summarized, in both absolute values and percentage change from the 2010 base case, in Table 5 and Figure 3 below.

Table 5. Sensitivity test results: Trips and Veh-km

Model runs	Trips*	Veh-km*	Trips**	Veh-km**
Base 2010	15,083	120,444		
P5 2015	15,317	131,400	1.55%	9.10%
P50 2015	15,354	125,746	1.79%	4.40%
P95 2015	15,613	135,227	3.51%	12.27%
P5 2020	14,722	143,515	-2.39%	19.16%
P50 2020	15,658	131,357	3.81%	9.06%
P95 2020	16,407	159,075	8.78%	32.07%
P5 2025	13,790	193,009	-8.57%	60.25%
P50 2025	15,898	135,202	5.40%	12.25%
P95 2025	17,687	184,803	17.27%	53.43%

* Thousands **Percentage change from Base 2010

As can be seen, the increasing uncertainty over time, reflected in the increasing spread of the p5 and p95 of the variables distributions, results in increasing variability of the output results. For instance, with respect to the number of trips in 2015, the p5 output shows an increase lower than the corresponding p50, 1.55% as compared to 1.79%, whilst the p95 output is 3.51% higher than the 2010 base case. The p5 2020 scenario produces instead a decrease in the number of trips of 2.39% as compared to the 2010 base case. In this case the decrease of fuel prices does not compensate for the decrease in population and GDP. Instead, p95 results for 2020 scenario produce an increase in the number of trips by 8.78% as compared to 2010, due to the increase in the population and GDP values which more than compensates the increase in the fuel prices. The p5 and p95 results for 2025 show an even bigger spread, with values of, respectively, -8.57% and 17.27%, due to the big difference in population growth rates between the p5 and p95 2025, of -7.1% as compared to 7.8%.

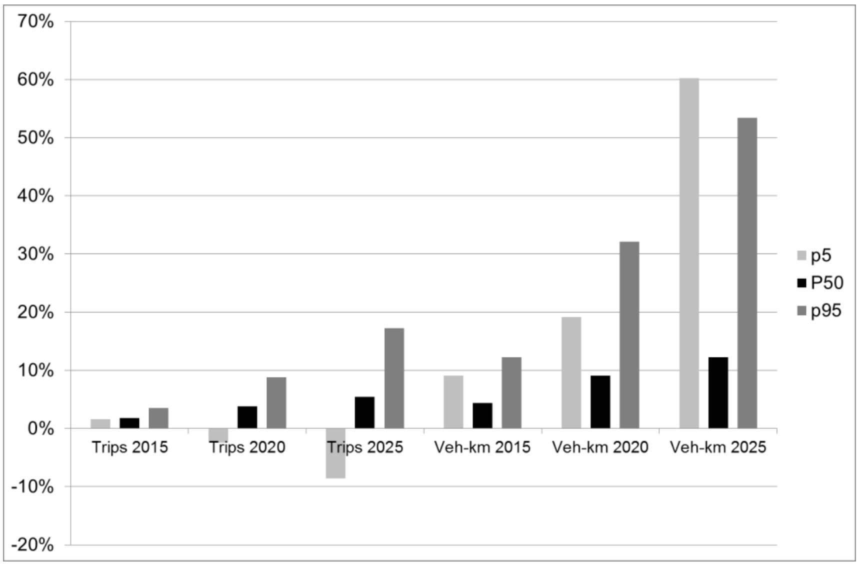

Figure 3. Trips and Veh-km percentage change from Base 2010

Unlike the number of trips, Veh-km p5 outputs show a higher increase than the corresponding base cases. For instance, in the p50 2015 scenario Veh-km is 4.4% higher than in the 2010 base case, whilst in the p5 2015 is 9.1% higher. This result reflects the increase in the car trip length following a decrease in travel cost per kilometre due to the reduced fuel prices. In fact, as can be seen in the Table 6 showing the average trip length by mode in percentage changes from the base 2010 scenario, while the average trip length for all modes reduces as compared to the base 2010 scenario, the length for the mode car driver increases. Furthermore, the p5 value for 2025 is higher than the p95 for the same year. Although counterintuitive, this result is explained by the increase in the average car trip length, which is higher in p5 2025 (51.56%) than in p95 2025 (21.28%). This difference in car trip length is primarily due to the big difference in the fuel prices between the two model runs. In fact, whilst p5 2025 petrol and diesel prices decrease by 9.3% and 15.3% respectively, p95 values increase by 10.5% and 16.7%, respectively. The difference in petrol and diesel prices between p5 2020 and 2025 can instead only partially explain the big difference between p5 2020 and 2025 Veh-km.

Table 6. Average trip length by mode (percentage change from Base 2010)

Model runs	Walk	Bike	Car Driver	Car Passenger	Public Transport
P5 2015	-3.64%	-2.25%	3.66%	-1.03%	-3.41%
P50 2015	-3.08%	-1.71%	0.33%	-1.11%	-2.71%
P95 2015	-3.68%	-2.35%	3.95%	-1.24%	-3.08%
P5 2020	-7.49%	-4.69%	13.85%	0.08%	-0.03%
P50 2020	-5.71%	-3.15%	2.79%	-0.30%	0.73%
P95 2020	-7.23%	-4.82%	13.86%	-1.56%	-0.41%
P5 2025	-11.61%	-7.90%	51.56%	-1.98%	-3.13%
P50 2025	-6.99%	-4.04%	3.08%	-0.71%	-0.85%
P95 2025	-8.94%	-6.44%	21.28%	-2.62%	-3.26%

Table 7 shows the results from the sensitivity tests related to the average speed (AvgSpeed), the free flow time (FreeTime) and the congested flow time (CongTime). As can be seen, with the network capacity held constant the increase in the overall traffic over time reduces the average speed. This is reflected in the congested time, which shows high variability throughout the different model runs.

Table 7. Sensitivity test results: Average speed, FreeTime and CongTime

Model runs	AvgSpeed	FreeTime*	CongTime*	AvgSpeed**	FreeTime**	CongTime**
Base 2010	53.94	53,652	5,321			
P5 2015	53.15	53,891	6,308	-1.46%	0.45%	18.56%
P50 2015	53.46	53,675	5,897	-0.90%	0.04%	10.82%
P95 2015	52.86	53,984	6,666	-2.00%	0.62%	25.28%
P5 2020	52.61	54,214	7,349	-2.46%	1.05%	38.12%
P50 2020	53.15	53,351	6,103	-1.47%	-0.56%	14.70%
P95 2020	51.54	54,356	8,484	-4.46%	1.31%	59.45%
P5 2025	50.22	55,595	12,231	-6.91%	3.62%	129.87%
P50 2025	52.82	53,231	6,487	-2.09%	-0.78%	21.92%
P95 2025	50.04	54,663	10,760	-7.24%	1.89%	102.22%

* Thousands of hours **Percentage change from Base 2010

Despite the limited amount of sensitivity tests produced, an attempt to infer the overall output uncertainty propagation over time was made by calculating the Coefficient of Variation (CV) for each of the outputs analysed above. The CV, corresponding to the SD divided by the mean, is a measure commonly applied to quantify the level of uncertainty of a distributed variable. The results are summarised in Table 8 and graphically described in Figure 4 below. As can be seen, the CV increases over time for all the model outputs investigated. However, while for the average speed and the free time this increase is scarcely noticeable, for other model outputs, and in particular for the congested flow time and the Veh-Km, the CV increase is clearly visible. This result is of great importance, considering the high relevance that these two model outputs have in transport project and policy appraisals. Furthermore, the applied methodology allowed to reproduce an increase over time of the output uncertainty, as can be seen by the non-linear propagation pattern over time. It is worth to notice that, as can be reminded from Table 2, not all the socio-economic variables investigated showed an increase in uncertainty over time, in fact only population and fuel prices. Overall, this suggests higher sensitivity of the NTM outputs investigated to the population and fuel prices values.

Table 8. Coefficient of variation by year and model output

Year	Trips	Veh-km	AvgLength	AvgSpeed	FreeTime	CongTime
2015	0.011	0.038	0.004	0.006	0.003	0.065
2020	0.054	0.106	0.029	0.015	0.010	0.195
2025	0.123	0.231	0.110	0.029	0.022	0.460

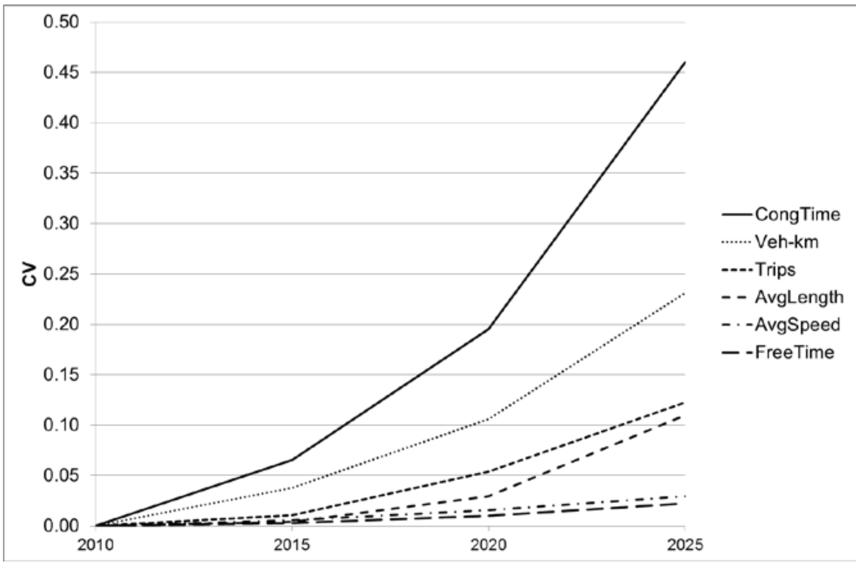

Figure 4. CV propagation over time

In addition to the uncertainty propagation pattern over time, two 2025 socio-economic sensitivity tests were implemented, based on the results of the Latin Hypercube sampling summarised in table 4: (1) low fuel prices (p5) combined with high GDP and employment levels (p95), and (2) high fuel prices (p95) combined with low GDP and employment levels (p5). While test (1) intends to simulate the effects of low petrol prices as potential driver for economic growth, test (2) instead is meant to reproduce the negative effects of high petrol prices on the national economy. Table 9 summarizes the total number of trips resulting from the implementation of the two sensitivity tests. The sensitivity test (1) produced, as compared to the p50 2025, a modest increase in number of trips of 0.39%. With respect to the results from the sensitivity test (2), which was expected to reduce the demand of transport, the number of trips remains substantially stable as compared to the base case (0.05%). To investigate further this topic, two more sensitivity tests were then implemented representing, everything else staying constant at the base case levels, different population growth rates: (3) simulates an increase in the population (p95) as compared to the base case, whilst (4) a decrease (p5). As can be seen, the results from both model runs significantly differ from the base case. Indeed, as compared to the base case, the variation in the number of trips for sensitivity tests 3 and 4 is, respectively, of +11.08% and -13.41%. Thus, the model sensitivity to the variation of population growth rates is higher than that resulting from the combined variation of fuel prices, GDP and employment growth rates. This seems to identify the population as the dominant variable affecting the model, among those examined.

Table 9. Sensitivity analysis results (2025)

	Base	Sensitivity test 1	Sensitivity test 2	Sensitivity test 3	Sensitivity test 4
Trips*	15,898	15,959	15,905	17,660	13,765

* Thousands.

6. Conclusions

The study described in this paper investigated the uncertainty in the NTM forecasts caused by the uncertainty of the forecasts of the model socio-economic variables, namely population, GDP, employment and fuel prices. The choice of using a large-scale transport model to run the analyses aimed to increase the amount of evidence on the topic related to large-scale models. In fact, despite their importance as support for strategic transport related decisions, there are not many studies investigating uncertainty analysis on large-scale models.

The analysis was carried out through stochastic simulation combined with model sensitivity analysis. The variables' growth rate forecast uncertainty was quantified through Monte Carlo simulation for 5 year intervals over a period of 15 years. A method to describe how uncertainty grows over time was implemented by computing SD for different time intervals of 5, 10 and 15 years. The rationale was to reflect the progressive decrease in the modeller's knowledge about the model components' future state by varying the SD to be used in the Monte Carlo simulation.

The SD were calculated based on the inaccuracies of past forecasts and past time series. This is a limitation in the sense that this approach allows to investigate only the component of the future uncertainty which is assumed to be rooted in the observed past variability. Besides, one source of uncertainty which should be addressed is the uncertainty variation over time of how individuals react to the different future values of the socio-economic variable. This is represented in the model by the calibrated parameters used, for instance, in the passenger and assignment models. On the top of our knowledge no attempt has been made so far to address such issue.

The model outputs analysed were (i) the total number of trips and vehicle-kilometres, (ii) the trip average length by mode, and (iii) the average speed, free and congested time. The resulting temporal pattern of uncertainty was neither linear nor similar for the different model outputs investigated. In particular, vehicle-kilometres and congested time showed a higher increase in uncertainty over time.

Despite the results from the analysis described in this paper cannot be generalised, being related to a specific transport model, they nevertheless highlight two key points. First, they confirm the importance of implementing uncertainty analysis with a dynamic approach as part of a transport modelling process. In fact, different transport related projects may focus on different model outputs which have different temporal uncertainty propagation patterns. Thus, considering the long time horizon of transport project assessments, quantifying the uncertainty propagation pattern over time for key model outputs becomes strategically important. Second, the method suggested in this study to implement Monte Carlo simulation uncertainty analysis with a dynamic approach proved to be doable, so allowing such analysis to be conducted.

Acknowledgements

The authors gratefully acknowledge the financial support by the Danish Council for Strategic Research for the project "Uncertainties in Transport Project Evaluation" and the constructive and insightful comments by three anonymous reviewers on previous versions of the manuscript.

References

Armoogum, J. (2003). Measuring the impacts of uncertainty in travel demand modelling with a demographic approach. Proceedings of the *European Transport Conference*, Strasbourg.

Ashley, D. (1980). Uncertainty in the context of highway appraisal. *Transportation*, 9, 249-267.

Brundell-Freij, K. (2000). Sampling, specification and estimation as sources of inaccuracy in complex transport models - some examples analysed by Monte Carlo simulation and bootstrap. Proceedings of the *European Transport Conference*, Cambridge.

Daly, A. (1998). Prototypical sample enumeration as a basis for forecasting with disaggregate models. *Transport Planning Methods*, 1(D), 225-236.

De Jong, G., Daly, A., Pieters, M., Miller, S., Plasmeijer, R. and Hofman, F. (2007). Uncertainty in traffic forecasts: literature review and new results for The Netherlands. *Transportation*, 34, 375-395.

Hugosson, M.B. (2005). Quantifying uncertainty in a national forecasting model. *Transportation Research Part A*, 39, 541-547.

Krishnamurthy, S. and Kockelman, K.M. (2003). Propagation of uncertainty in transportation land use models: investigation of DRAM_EMPAL and UTPP predictions in Austin, Texas. *Transportation Research Record*, 1831, 219-229.

Kroes, E.P. (1996). Some issues in traffic forecasting for privately financed infrastructure. Proceedings of the *PTRC European Transport Forum*, Brunel University.

Leurent, F. (1998). Sensitivity and error analysis of the dual criteria traffic assignment model. *Transportation Research Part B*, 32, 189-204.

Matas, A., Raymond, J. and Ruiz, A. (2011). Traffic forecasts under uncertainty and capacity constraints. *Transportation*, 39(1), 1-17.

Petrik, O., Moura, F.M., Ghebrehiwot, Y., Silva, J., (2012). Measuring uncertainty on the Portuguese high-speed railway demand forecast models. Proceedings of *13th International Conference on Travel Behaviour Research*, Toronto.

Pradhan, A. And Kockelman, K.M. (2002). Uncertainty propagation in an integrated land use–transportation modelling framework. *Transportation Research Record*, 1805, 128-135.

Rasouli, S. and Timmermans, H. (2012). Uncertainty in travel demand forecasting models: literature review and research agenda. *Transportation letters*, 4, 55-73.

Rich, J. (2011). *Introduction to transport models – Application with SAS Software*. Lulu Press, Denmark.

Rich, J., Nielsen, O.A., Brems, C. and Hansen, C.O. (2010). Overall design of the Danish national transport model. Paper presented at the *Annual Transport Conference*, Aalborg (DK).

Rodier, C.J. and Johnston, R. (2002). Uncertain socio-economic projections used in travel demand and emissions models: could plausible errors result in air quality nonconformity?. *Transport Research Part A*, 36, 613-631.

Walker, W.E., Harremoes, P., Rotmans, J., van der Sluijs, J.P., van Asselt, M.B.A., Janssen, P. and Krayer von Krauss, M.P. (2003). Defining uncertainty; a conceptual basis for uncertainty management in model-based decision support. *Integrated assessment*, 4, 5-17.

Zhang, T., Xie, C., Waller, S.T. (2011). Integrated equilibrium travel demand model with nested logit structure; fixed point formulation and stochastic analysis. *Transportation research record*, 2254, 79-96.

Zhao, Y., Kockelman, M. (2002). The propagation of uncertainty through travel demand models; an explanatory analysis. *Annals of Regional Science*, 36, 145-163.